Data Science Applications in Games

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Introduction to Data Science in Gaming

Data science is a multidisciplinary field that uses mathematics, statistics, and computer science techniques to analyze and interpret complex data sets. The primary focus of data science is to extract meaningful insights or meaningful information from data. One of the most important application areas of data science is the digital gaming industry, where large amounts of data are processed and results are customized according to the data. The use of data science techniques in the digital gaming industry is increasing to optimize game design and improve the game environment and player experience. The possibilities provided by data science have become a cornerstone for the industry as game developers, publishers, and marketers (Wallner & Drachen, 2023). The digital game industry uses a vast array of data types to improve both player experience and business outcomes. Some of the data sets used in gaming environments include gameplay data, player behavior data, demographic data, purchasing data, telemetry data, A/B testing data, social data, feedback data, market and competitor data, emotion and biometric data, and VR/AR interaction data.

Game Data

Game data obtained from player actions and interactions in the game environment can provide valuable insights for game developers and analysts (Kriglstein, 2019). For example player movements, clicks, actions, heatmaps, completion rates for levels or quests, in-game purchases and item usage, etc. The collected game data helps developers understand how players interact with the game. This data can be used to fine-tune game mechanics, balance the game difficulty, and improve overall game design.

Player Behavior Data

Player behavior data includes information that includes how players interact with the game environment, patterns, preferences, and habits. Obtaining player behavior directly is a difficult process. Therefore, inferences about player behavior are attempted to be made using a wide variety of data. In this context, data such as session length and frequency, time spent on specific game features or modes, choices made in decision-based games, player retention, and churn rates, as well as social interactions in multiplayer games (such as chatting and team building) are used to determine player behavior. With this player behavior data, game developers can produce data-based solutions for processes such as keeping players in the game, adjusting game difficulty, and creating personalized content for individual users.

Demographic Data

Data obtained regarding the identity of the player using the information provided by players when creating a user account or information collected through surveys is called demographic data. This data includes information such as age, gender, location, game platforms, and device types (Kaye, 2019). This data obtained is important for developers and marketers. Developers and marketers can determine their target audience by analyzing demographic data. They can then make adjustments to the target audience in game features, content, and marketing campaigns. In addition, this demographic data obtained can also be used in the development of localization strategies and platform-specific optimizations.

Purchasing Data

Purchasing data consists of data on virtual currency transactions, product trading patterns, marketplace activity in games with virtual economies, trading, and purchasing behaviors (Cai et al., 2022). Purchasing data helps developers optimize in-game purchasing processes, helping players balance gameplay and purchasing. This helps game developers balance virtual economies and design fair and engaging monetization models.

Telemetry Data

Telemetry data is collected from both the game client and server to monitor performance, player activity, and in-game events (Lim & Harrell, 2014) over distance. This includes many parameters for player behavior, server performance metrics, network latency, connection issues, hardware performance (such as FPS and CPU usage), crash reports, and error logs. Telemetry data is used to optimize game performance, identify technical issues, and ensure smooth gameplay, particularly in online or multiplayer games.

A/B Testing Data

A/B testing data is collected from experiments in which two or more game variants are tested on different player groups. For example, this can involve testing various user interface (UI) designs or button placements, comparing engagement levels for different reward systems or pricing models, and variations of in-game events or levels. A/B testing data enables developers to evaluate which game features or designs perform better with players, leading to more informed decision-making during the development process.

Social Data

Social data is related to player interactions within social features or on external platforms. For example, friends lists, chat data, social invites, team interactions in multiplayer games, social media sharing (such as achievements and screenshots), forums, reviews, and player feedback. Social data assists developers in enhancing multiplayer experiences, community features, and player engagement within the game's ecosystem (Schiller et al., 2019). Additionally, it supports marketing strategies by word-of-mouth or viral spread.

Feedback Data

Feedback data is qualitative data that is gathered from player feedback, reviews, or in-game communication. For example, data gathered from platforms (Steam, App Store, Play Store, etc.), surveys and feedback forms, sentiment analysis from social media or forums, and in-game feedback systems (e.g., post-level ratings). Feedback data makes it easier for developers to understand player satisfaction levels and identify undesirable situations. Positive feedback can enhance intrinsic motivation and long-term play by satisfying competence needs while negative feedback may increase immediate gameplay to improve short-term performance (Burgers et al., 2015).

Emotion and Biometric Data

Emotion and biometric data can be gathered from players' physical responses via emotion recognition software or biometric sensors (Granato et al., 2018). For example, facial expressions and emotional reactions, heart rate, skin conductance or eye movements, and stress or excitement levels can be considered as emotion and biometric data. This data can allow developers to dynamically adjust the game, based on real-time emotional feedback, increasing immersion and personalizing the player experience.

VR/AR Interaction Data

VR/AR Interaction Data is collected from players' interactions with virtual and augmented reality environments. For example hand and head tracking movements, gaze tracking, spatial interaction, and physical gestures type interactions. VR/AR data provides insights into how players interact with 3D environments, helping developers create more immersive and intuitive experiences.

As a result, data collection methods are playing a revolutionary role in the digital gaming industry. Through various data collection methods such as in-game telemetry, A/B testing, player profiling, feedback, and biometric data, developers can optimize game design by better understanding player behavior and preferences.

Data Collection Methods in Gaming

Various methods and approaches are available for collecting game data, including game telemetry, a/b testing, player tracking, event logging, data streaming within games, real-time data collection, game analytics tools, and player profiling techniques. These techniques can have a quantitative or qualitative approach. Game data can focus on development, player satisfaction, game publishing and distribution, and game prediction (Su et al., 2022). Data can be collected live from game-playing sessions and actual players. Examples of in-game data include performance metrics such as in-game movements, interactions, choices, time spent, points levels, and scores, as well as social interactions, economic preferences, bugs and errors, and data related to bots. User comments about games on external platforms are also considered crucial data for developers (D. Lin et al., 2019). These data can provide valuable insights into game satisfaction, enabling the collection and analysis of various aspects related to user contentment.

One of the data collection methods used in game environments is telemetry data. Telemetry data is widely used in game development processes to analyze player behavior, optimize game design, manage monetization strategies, anticipate behaviors, and detect fraudulent activities (Drachen, 2015; Lynn, 2013; Sifa et al., 2018). Using telemetry data, behavioral profiles, and player clusters can be identified. This facilitates the classification of player actions and preferences (Drachen et al., 2014; Kabakov et al., 2014; Sifa et al., 2018). By analyzing telemetry data, developers can predict player engagement by identifying patterns of gameplay and in-game behavior (Bauckhage et al., 2012). On the other hand, by integrating this with traditional user testing protocols, a more comprehensive analysis can be achieved through the effective use of insights into player behavior (Drachen, 2015; Lynn, 2013). Finally, in evaluating the data collected via telemetry, the application of visualization techniques simplifies the identification of the data, helping to reveal hidden patterns and errors in game design as well as player behaviors (Mirza-Babaei et al., 2014; Moura et al., 2011; Seif El-Nasr et al., 2013).

Developers develop different versions of games, and it may be necessary to conduct statistical studies to reveal the differences between these versions. A/B testing is a data collection and evaluation method used to determine which system version has the best features for specified features (Viljanen et al., 2017). Researchers use A/B testing to gather product/system data and user-centric data ("A/B Testing," 2017; Quin et al., 2023), page load times, and service latency (M. Liu et al., 2019), number of sessions per user, and absence time (Drutsa et al., 2015), playing time, and leveling speed (Drachen et al., 2014) to analyze and draw inferences. A/B tests have hypotheses that claim one situation gets better results. Based on this hypothesis, two game environments/levels/designs are developed and presented to players. With A/B testing, the results obtained from a specific group can be generalized. This can only be made possible with correct sampling. Data science aims to achieve this goal by optimizing factors such as the right sample size, test period, and number of variations (Drovandi et al., 2017). After finding the sample size, advanced data science techniques are used to collect, clean, and process large-scale data (El-Nasr et al., 2021) generated in A/B testing sessions correlated with the hypothesis. Data science provides tools and methods to process these data, provides deep insights, and is useful for measurement and analysis (Gupta & V., 2020). A common method in A/B testing is frequentist inference (Johari et al., 2015), which is based on the assumption that observations are independent and binary or normally distributed. Another method is the Bayesian approach which adds flexibility to studies limited by p significance value. The Bayesian method enables the control of external factors that may affect the results and supports the measurement of differences between variations more effectively (Johari et al., 2015). Probabilistic reward methods (Martín et al., 2021) are used in situations where there is uncertainty and incomplete information on A/B testing. In the context of these and similar data collection and analysis methods, data science contributes to the most effective execution of the process by providing both technical and analytical support in the A/B tests.

In addition to game telemetry and a/b testing, eye tracking and biometric data are also used to collect game data. Eye tracking technology is used to assess emotional responses by analyzing eye movements, fixations, saccades, and pupil diameter during gameplay (J. Z. Lim et al., 2022; Renshaw et al., 2009; Skaramagkas et al., 2023; Tarnowski et al., 2020). Biometric measures such as galvanic skin response (GSR), electrodermal activity (EDA), and heart rate variability are employed to objectively assess emotional activation and engagement levels during gameplay (Ivanina et al., 2023; López-Gil et al., 2016; Simoes & Gomes, 2023; Vazquez et al., 2022). These technologies provide valuable insights into player engagement and emotional activation.

Another data collection method in digital games is event logging. The event log is used to track game errors and performance issues. The data obtained from this process reveals hidden information about player behavior, player performance, and system functionality (Smeddinck et al., 2013; Yu et al., 2022). Analyzing the information in the event logs helps to diagnose errors within the game and enhance the overall gaming experience for players (Cheong & Young, 2006).

As a data collection method, streaming can provide valuable data, particularly regarding the influence of streamers on player engagement. For instance, streaming data from platforms such as Twitch facilitates the capture of player interactions and community dynamics, offering a deeper understanding of player engagement (Micallef et al., 2024). Additionally, data streaming can uncover correlations between streaming activity and in-game performance (Matsui et al., 2020).

Player profiling techniques are an essential tool that encompasses a wide range of methodologies for understanding player behavior and preferences in gaming. For this purpose, techniques such as behavioral data obtained from in-game logs, surveys and questionnaires, multimodal analysis, and machine learning algorithms are used. One prominent approach involves the utilization of behavioral data obtained from in-game logs, which can reveal patterns in player actions and decision-making processes (Trepte & Reinecke, 2011). Additionally, surveys and questionnaires are frequently employed to gather self-reported data on player motivations, preferences, and psychological states, allowing researchers to correlate these factors with gameplay behavior (Jeong et al., 2020; Trepte & Reinecke, 2011). Moreover, advanced techniques such as multimodal analysis combine behavioral experiments with survey data to evaluate cognitive effects and player experiences (Jeong et al., 2020).

To summarize, various methods for collecting game data include telemetry, player tracking, event logging, and data streaming. Each of these methods provides insights into player behavior and game performance. Telemetry data helps developers to optimize game design and manage monetization strategies, while A/B testing evaluates the effectiveness of different game versions. Eye tracking and biometric measures assess player emotional responses, and event logging tracks performance issues and player interactions. Additionally, data streaming reveals the impact of streaming on player engagement, and player profiling techniques, including surveys and machine learning, help understand player preferences and inform game design. The analysis of gaming data through these diverse methodologies significantly contributes to the understanding of player behavior and the optimization of game design. However, to evaluate the effectiveness of these insights and strategies, game developers and studios must depend on key performance indicators (KPIs) to assess the success of their games.

Game Analytics: Key Metrics and Key Performance Indicators

Key metrics or Key performance indicators (KPIs) are quantifiable metrics to evaluate business, healthcare, and project management-critical initiatives, processes, or objectives. KPIs are instrumental in assessing performance in various sectors, including healthcare to evaluate established standards (Rego et al., 2023), and different industries to form the basis of payments (Lop et al., 2017). One notable application of KPIs is within the gaming industry. In the game industry, key metrics can range from daily and monthly active users (DAU/MAU), retention rate, churn rate, session length, average revenue per user (ARPU), conversion rate, gameplay metrics, virality, player lifetime value, technical performance metrics, engagement metrics, and cognitive and behavioral metrics.

Certain metrics offer insights into player interactions with a game, which are essential for understanding retention rates (Aleem et al., 2016b, 2016a). Another significant engagement metric is session length, which measures the average time players spend in a game during a single session. This metric can indicate how compelling and immersive the game experience is (Koivisto et al., 2023). Also, daily and monthly active users (DAU/MAU) are commonly used to measure the number of unique players engaged with a game over specific time periods and provide insights into the game's popularity and player retention (H. X. Liu & Wagner, 2023).

Monetization strategies are also an important KPI in the gaming industry. In the gaming industry, metrics such as average revenue per user (ARPU), player lifetime value, and conversion rate are commonly used to evaluate the financial success of a game. These metrics help developers understand how much revenue they can expect from each player over time and can also guide decisions regarding pricing models and in-game purchases (Klimas, 2019; Krstić, 2021). The conversion rate is the proportion of free-to-play players who transition into paying users. This metric tracks the percentage of players who make in-game purchases and provides information about the effectiveness of monetization strategies (Junaidi et al., 2018).

Gameplay metrics provide insights into player behavior and performance within the game. These include metrics such as the number of games played, win/loss ratios, and in-game achievements (Koivisto et al., 2023; Lameman et al., 2010). Satisfaction as an engagement metric can affect games' reputation and longevity. In particular, the fun factor, which evaluates players' overall enjoyment and emotional response, plays a crucial role in understanding this satisfaction (Strubberg et al., 2020). Furthermore, engagement metrics extend beyond individual experiences and include brand loyalty and community engagement, which can be measured through social media interactions, community forums, and player feedback.

Technical performance metrics can be load times, frame rates, memory-CPU-GPU usage, network latency, response time, error rates and crashes, and rendering performance. These metrics provide insights into the game's technical aspects, which significantly influence player satisfaction and engagement. According to Junaidi et al. (2018), load times refer to the duration it takes for a game to start or transition between different levels or scenes, and optimizing these load times is essential for maintaining player engagement. Additionally, network latency, defined as the delay between a player's action and the game's response, is often influenced by internet connection or server speed and can greatly affect gameplay. Junaidi et al. (2018) also emphasize the importance of monitoring errors and crashes during gameplay, as high error rates may indicate underlying issues that need to be addressed to improve the overall player experience. Frame rate indicates how many frames are rendered by the game in one second. A higher frame rate typically results in smoother gameplay, enhancing the player's experience. Conversely, a lower frame rate creates choppy visuals and affects gameplay performance negatively (Koulaxidis & Xinogalos, 2022). Koulaxidis & Xinogalos (2022) also highlight that memory usage tracks the RAM consumed by the game, with high usage potentially causing lag or crashes, especially on resource-limited devices. Similarly, metrics for CPU and GPU (rendering performance) usage indicate the amount of processing, and excessive usage can slow down performance. Tracking both metrics helps developers optimize the game across platforms.

Many metrics, most notably retention, and churn rates are important parameters used in the gaming industry. These indicators also serve as critical inputs for predictive modeling efforts. For example, the ability to predict player churn relies heavily on analyzing in-game behaviors and engagement metrics that KPIs can effectively capture. Being able to predict these values in advance can help game developers make decisions in advance, making games more appealing.

Predictive Modeling in Games

Churn prediction has long been an area of interest in predictive modeling for digital games, especially those using a free-to-play model. In this area, research has been conducted to predict churn with advanced statistical models and machine learning techniques. Roohi et al. (2020) conducted AI-assisted studies to determine the link between game difficulty and player retention. In order to determine player preferences and interests, it is necessary to analyze in-game interactions and player behaviors well. For example, Chen et al. (2018) worked on player activity prediction using time series forecasting with deep learning. This level of application can be used by developers to create game experiences that are customizable and built around the goal of improving player satisfaction and retention. Studies regarding the regularity of player engagement have demonstrated strengthening churn prediction through the mixing of playtime records integration and behavioral data (Yang et al., 2019).

In some studies on churn predictions and player behavior analysis, neural networks, logistic regression and various algorithms were used to analyze. For example, in the game Candy Crush Saga, how each player performed was analyzed with machine learning algorithms, and customizations were made for the game difficulty for each player. Additionally, Guo's research on player churn prediction emphasized that using different ensemble learning methods showed an increase in prediction performance, as it combined the strengths of multiple models (Guo et al., 2024). These advances in machine learning not only enhance the accuracy of predictions but also provide actionable insights for game developers to improve their strategies.

There are also studies on estimating the outcome in games, that is, the probability of winning. These studies aim to present pre-game and in-game predictions. They are matchmaking systems that focus on matching teams at the beginning of pre-game predictions and try to keep the probability of winning at 50%. These aim to analyze team data, make a win prediction, and match teams with similar values. For example, in DOTA A2, a Multiplayer Online Battle Arena (MOBA) game, telemetry data such as hero selection before the game and post-game end-of-game statistics (score, experience, kill rate) were analyzed with machine learning methods such as Logistic Regression and Random Forest Classifier, and end-of-game predictions were obtained (Kinkade et al., 2015). In another study, data such as time, number of remaining players, team numbers, equipment value, health status, and equipment number from CS-GO in-game data were taken instantly and analyzed with decision trees and Logistic Regression methods, and a dynamic prediction structure was provided (Makarov et al., 2018). Another approach to prediction is the use of real sensor data. In the study conducted by Smerdov et al. (2021), sensor data was processed with the machine learning method and an attempt was made to predict win/lose situations based on player burnout. In the study conducted on the League of Legends game, sensor data for electromyography, eye tracking, seat movements, galvanic skin response, heart rate, facial temperature, electroencephalography and room temperature, humidity, and CO2 levels were used and a structure that can provide feedback for the person to play more defensively in the event of a loss was developed using a model developed with machine learning. Such prediction models improve the gaming experience by helping players understand their situations and the effects of their strategic choices during the game. In the future, it is expected that these models will be applied to more game types and enrich the player experience.

In digital games, predictive modeling is an umbrella term that encompasses a wide variety of high-end statistical and machine-learning tools used to predict player behavior and this research field is very vast. Such integration will consequently allow game developers to enhance player acquisition, improve player retention, optimize game design, and eventually, hit higher revenues. This is a manifestation of the fact that the gaming industry at present stands at an evolutionary crossroads and we can witness likely more increase in the application of predictive models here, hence this area calls for more research efforts and innovation.

Churn, win/lose, matchmaking predictions, and player behavior analysis are deeply interconnected areas within the field of game development, both contributing valuable insights for improving player retention and overall engagement. While prediction focuses on identifying factors that lead players to leave the game or find the fairest match or analyze the user and make suggestions, behavior analysis delves into understanding how players interact with the game environment and detect losing interest, player strategies, key areas, points, or levels.

Player Behavior Analysis

Player behavior analysis in video games utilizes a wide array of methods, providing crucial insights for developers to enhance user experience. These methods can be categorized into several key approaches, including statistical analysis, machine learning, spatial analysis, clustering, and visualization techniques. Each of these methodologies provides unique insights into player behavior, enabling developers to enhance game design, improve player engagement, and foster a more enjoyable gaming experience.

One of the foundational methods for analyzing player behavior is statistical analysis, which involves the application of various statistical techniques to derive insights from telemetry data. For instance, Bauckhage et al. (2012) emphasized the importance of analyzing distributions of total playing times to understand how players lose interest in games. By examining these distributions, developers can identify critical points in gameplay that may lead to player disengagement, allowing for targeted interventions to retain players. In addition to statistical methods, mixed techniques have also gained prominence in the analysis of player behavior. For example, Canossa et al. (2018) employed a mixed method using telemetry analysis, sequence mining, and clustering to develop detailed player profiles in “Tom Clancy’s The Division.” using 52 event types and 10.000 players’ data. This method allows us to understand usage or gameplay loops, which provide information about player behavior.

By analyzing player behaviors, players can be clustered based on behavioral patterns (Ahmad et al., 2019). These patterns allow for a deeper understanding of player strategies and interactions, which are essential for improving game design and player retention. In the player behavior analysis conducted on 6 million players and 3007 games (Sifa et al., 2014), playing times and game ownership data were examined and cluster analysis showed that only 1/3 of the players distributed their time equally among 3 games, while the rest played a single game. In the same study, it was determined that the playing time was divided into four main clusters, and most games, except for a few, were played for several hours. Additionally, Sifa et al. (2013) applied clustering methods to analyze the behavior of over 62,000 players in “Tomb Raider: Underworld,” revealing how player behavior evolves throughout the game.

Building on these techniques, Archetypal Analysis is another method used to examine player data. It is a multivariate data analysis technique that identifies idealized extreme points, or archetypes, to explain observations in a dataset. In the paper by Pirker et al. (2016), which analyzes data from 5000 players and includes 11 activity types such as frequently performed actions, discoveries, points, and time, archetypal analysis is used to understand the evolution of player types and behavior over time and across missions.

Complementing archetypal analysis, spatial analysis offers a deeper insight into player behavior, especially in games with intricate environments. Drachen & Canossa (2011), using data from 28,000 players, introduced spatial analysis of gameplay metrics as a novel approach to user-experience testing. By analyzing the spatial distribution of player actions, developers can identify key areas of interest within the game world. This understanding helps inform both level design and gameplay mechanics, guiding players through the game environment more effectively. In a similar vein, Jim Blackhurst (2011) utilized spatial data from 11.3 million Just Cause 2 players to create heatmaps and 3D visualizations of player death locations, focusing on impact-related deaths (Figure - 1). Overcoming challenges related to large datasets and memory constraints through tools like Processing and OpenGL, Blackhurst was able to render millions of data points in real time. This visualization work enhanced the understanding of player behavior by revealing how players interact with the game environment and identifying significant points of interest.

Figure 1
Visualization of 11.3 Million Players' Death data

Visualization techniques play a crucial role in analyzing player behavior by effectively communicating complex data insights. Moura et al. (2011) observed that traditional methods, such as heatmaps and bar charts, often fall short of representing the temporal progression of player actions. To overcome this limitation, they suggested more dynamic visualization techniques that capture the evolution of player behavior over time. Such methods can greatly enhance developers' understanding of player interactions and inform more strategic design decisions. Additionally, Mirza-Babaei et al. (2014) conducted a case study and proposed a unified visualization approach that integrates qualitative and quantitative data from players' emotional experience from playtesting, offering a more comprehensive understanding of player behavior.

Another significant method for analyzing player behavior is data mining from game telemetry. Lim & Harrell (2014) collected and analyzed 51 types of game metrics including social platform interactions from 219 players to uncover underlying social identity and behavioral patterns. The analysis revealed significant relationships between in-game behavior and social networking interactions, explaining variances in players' number of friends, uploaded screenshots, and videos at rates of 35.1%, 49.6%, and 39.2%, respectively. Furthermore, Hadiji et al. (2014) used twenty million play sessions' telemetry data from five games to predict player churn. The study employs data mining techniques to analyze player behavior and predict churn in freemium games and machine learning algorithms to build predictive models that enhance the understanding of factors influencing player churn.

In conclusion, the analysis of player behavior in video games encompasses a diverse array of methodologies, including statistical analysis, machine learning, spatial analysis, visualization techniques, and user profiling. Each of these methods contributes to a comprehensive understanding of player interactions and preferences, enabling developers to create more engaging and satisfying gaming experiences. By integrating statistical, machine learning, and spatial analysis techniques, developers can not only predict player behavior but also optimize engagement in real-time, ensuring a more cohesive and satisfying gaming experience. To combine these insights, it's clear that integrating adaptive gameplay with advanced analytics offers a powerful toolset to increase player satisfaction. By leveraging methodologies like machine learning and spatial analysis to track player behavior, developers can create dynamic, personalized experiences where players feel a sense of ownership and satisfaction through a tailored gaming experience.

Personalization and Recommendation Systems

In digital games, adaptive gameplay is essential in facilitating personalization and enables the game to change its mechanics and difficulty according to the abilities of the player. For instance, Zhu & Ontañón (2020) have demonstrated that personalized game experiences can largely grow satisfaction and retention rates among players and so players are more willing to keep playing a game that also adjusts itself to their personal requirements. For example, games like "Minecraft" impel a rather strong sense of ownership and a deep commitment as players are given the option to customize their game experience exactly how they want it.

Adaptive gameplay requires personalization which can give players recommendations of in-game items, tasks, or challenges that suit what they need based on their previous interactions and preferences. This is typically done using collaborative filtering solutions analyzing player data to see what correlations can be made for suggestions. Blocker et al. (2014) discuss how knowing what players like can help with creating better interventions and design strategies, especially for different player types. Through data analytics, developers can craft a more personalized experience that will hook players and keep them playing and investing further. A mobile game, Clash Royale, recommends decks personalized using customized card recommendations based on a player's win-loss history and playstyle preference. In fact, research has shown that games designed with the overall player experience in mind are more likely to provide a degree of control and immersion necessary for long-term engagement (Radhakrishnan et al., 2020). Finally, player feedback can be integrated into the design process serves to improve certain parts of the game and update it accordingly so that it always fits with its audience (Hazar, 2018).

Developers should ensure that these systems keep the privacy and data security of players at paramount importance. A major ethical issue in data collection is transparency around the practice and ensuring that players have a high level of ownership over their data. In closing, personalization and recommendation engines allow digital games to better engage with players by way of adaptive gameplay, dynamic difficult tuning, and tailoring personalized content recommendations. By using collaborative filtering and player-centric design, developers can create games that appeal to specific people, keeping their audience happy and playing longer. As video games continue to evolve, the need for these systems is expected to grow even more in the coming years, meaning constant research and innovation is required to serve this dynamic new player base. As video games increasingly embrace complex customization features, developers and researchers are also focusing on optimizing game mechanics. Leveraging data to balance gameplay elements can increase player satisfaction. Also it supports a fair and engaging experience for all players.

Balancing Game Mechanics Using Data

Data supports game design by helping developers to balance the mechanics of a game. It also guarantees digital game operation fairness, competitiveness as well as player satisfaction. This is a process where data-driven methods are used to change aspects of game play like abilities, items, and level difficulty.

Automatic game balancing can be achieved with deep player behavior models that bring real-time adaptation to player performance and interactions (Pfau et al., 2020). This makes games more fun to play and helps ease the problems with player frustration or disengagement because there are imbalances within the game. Additionally, the way machine learning systems are incorporated into balancing game mechanics could lead to changes around individual player behaviors and preferences.

Another component of balancing game mechanics is matching player skill levels. It is essential in any system that players be matched against others with similar hardware and skill levels to provide fair and competitive matches. More advanced games like Overwatch attempt to match gamers with other players of similar skill levels by analyzing their performance data in-game using a refined matchmaking system. In MOBA games, pairing inexperienced players with experienced players can frustrate players (Vicencio-Moreira et al., 2015) and lead to an increased churn rate. This is especially critical when it comes to game enjoyment in first-person shooters (FPS) where they often dictate how much fun you can have playing. With the use of predictive algorithms, developers can understand player performance along with skill levels to create a great matchmaking environment that will surely help in retaining players.

Balancing game mechanics is a multifaceted process and requires data-driven balancing, matching player skills, and extensive balance testing methodologies. These tactics allow a lot of game devs to build better games that are more fun for many different players at higher and lower levels. As the gaming industry keeps changing, it will become increasingly important to think with data when balancing games, and there is a need for more research and innovation in this field.

Fraud Detection and Anti-Cheating Measures

Integrity in online gaming environments absolutely depends on protecting digital games from fraud and from cheating. With the rise of digital games, though, also comes a rise in cheating and other malicious actions that can shake the player's faith and deteriorate gameplay as a whole. One of the keys to maintaining a safe and clean environment in any type of digital game is enabling game security analytics to detect, find out, and suppress cheating. Analyzing player data and observing abnormalities in game play that may reveal cheaters, for example, the online first-person shooter game Counter-Strike: Global Offensive (CS-GO) uses complex behavior analysis to monitor player movements and actions for signs of cheating. Chapel et al. (2010) focus on detection techniques for cheating and talk about the need to base these in robust data-driven algorithms to identify suspect behavior and take appropriate action, using probabilistic methods as well. Such analyses can be used to provide a picture of how frequent and what kinds of cheating there is, which in turn helps developers direct their resources towards making the game more secure.

In digital gaming fair play is relatively important for which anti-cheat systems are indispensable. Utilizing a variety of methods to identify and mitigate cheating, these systems monitor player behaviors, analyze in-game data logs and implement machine learning algorithms. Alayed et al. (2013) presents a set of machine learning based cheat detection algorithms to recognize cheating patterns in internet First-Person Shooter games according to the player behaviors. These systems not only catch known cheats, but they continuously learn new ways to cheat so that the integrity of the system is maintained. Anomaly detection is another important part of cheating in digital games. By defining player behaviors over a reasonable span of time, developers can identify abnormalities suggestive of cheating. Sophisticated algorithms in games like Call of Duty: Warzone will monitor where players are moving and what weapons they have equipped, which can then flag oddities as potential cheats. This emphasis is especially valuable in multiplayer structures where one player's actions can greatly affect the experiences of others. S. J. Lee et al. (2021) argue that knowledge of these psychological issues could be made use of to enhance anomaly discovery initiatives by highlighting the impact of competitive motivation and self-training concerning what propels individuals to rip off habits. The experience is that developers can learn more about the psychology of cheaters and become better data analysts.

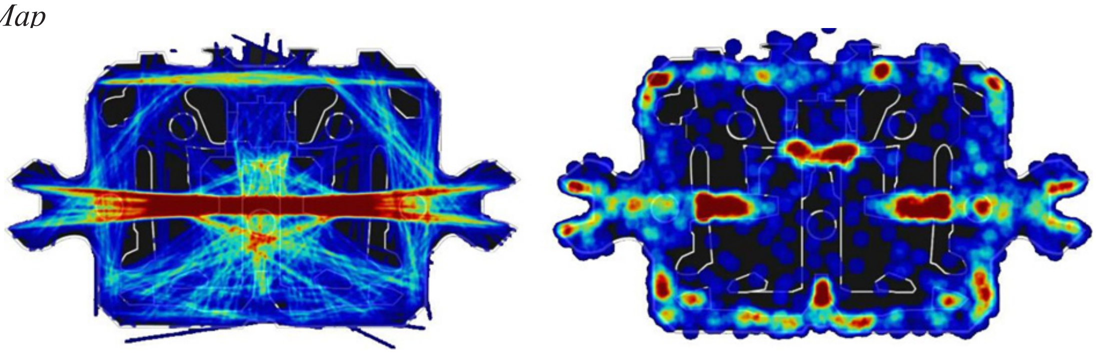
One key aspect of their anti-cheat solutions is bot detection, as one of the most common forms of cheating is automated scripts or bots that take over character gaming actions resulting in broken gameplay and unlevel playing field for normal non-pro gamers. McDaniel & Yampolskiy (2012) provide an example of such security for online games, the embedded CAPTCHA element prevents bot activity thus ensuring game integrity through technical solutions. The researchers also outline the use of machine learning in identifying first-person shooter bots, highlighting how these technologies can provide a sophisticated and effective approach to stopping cheating (Kanervisto et al., 2023). In summary, cheat detection and anti-cheat mechanisms in digital games are a complex multi-level process involving digital game security analytics, coupled with cheat-hacks/bots detection, anomaly identification, and bot networks tracking along with enforcement of fair play. Using data-driven methods and tools available in libraries can help developers in tackling cheating and ensuring that games stay fun. With the gaming ecosystem changing and maturing, further study and innovation in these fields will be necessary to combat upcoming fraud and cheating threats.

Data Visualization for Game Development

The visual system of humans has the most dedicated cells in the brain, reflecting its extensive neural resources allocated to processing visual information (Nassi & Callaway, 2009). This shows that people can perceive visual data faster than data from other sensory sources. At this stage, data visualization is a tool that makes it easier for people to perceive complex data (Silva, 2016; L. Zhou, 2023). Through data visualization, complex data transformed into visual formats can be easily perceived thanks to the innate abilities of the human visual system (Healey & Enns, 2012). Data Visualization is a subfield of visualization that focuses on the graphical representation of data. By transforming raw data into visual formats such as charts, graphs, and maps, data visualization makes it easier for people to see patterns, trends, and outliers (Gerela et al., 2022). Such as Figure 2, created by Halo® Game Data to visualize the sightline and kill of beam rifles on the Coliseum map (Halo Heatmaps, 2016). With this visualization, users can understand where to use or avoid the beam rifle and change their in-game strategies accordingly. This makes it easier to better analyze and communicate the information. Data visualization is an important component of data science that enables the discovery, analysis, and communication of complex data (Govind Shinde & Shivthare, 2024; Keim et al., 2013). Data visualization is one of the indispensable tools for a data scientist because it makes raw data easily observable.

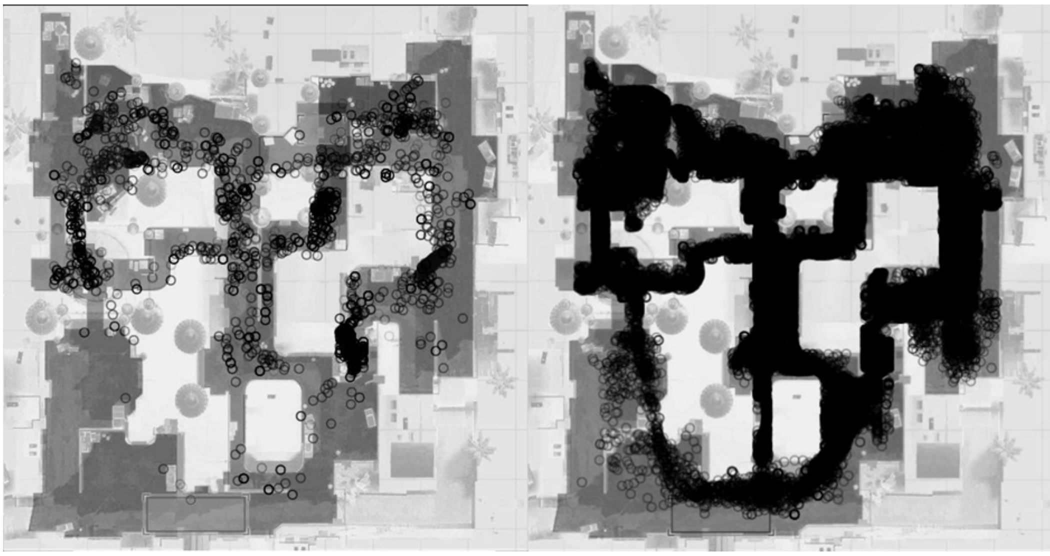
Figure 2

Visualization of the sightline (left) and death (rigth) map of a gun on Halo - Coliseum Map



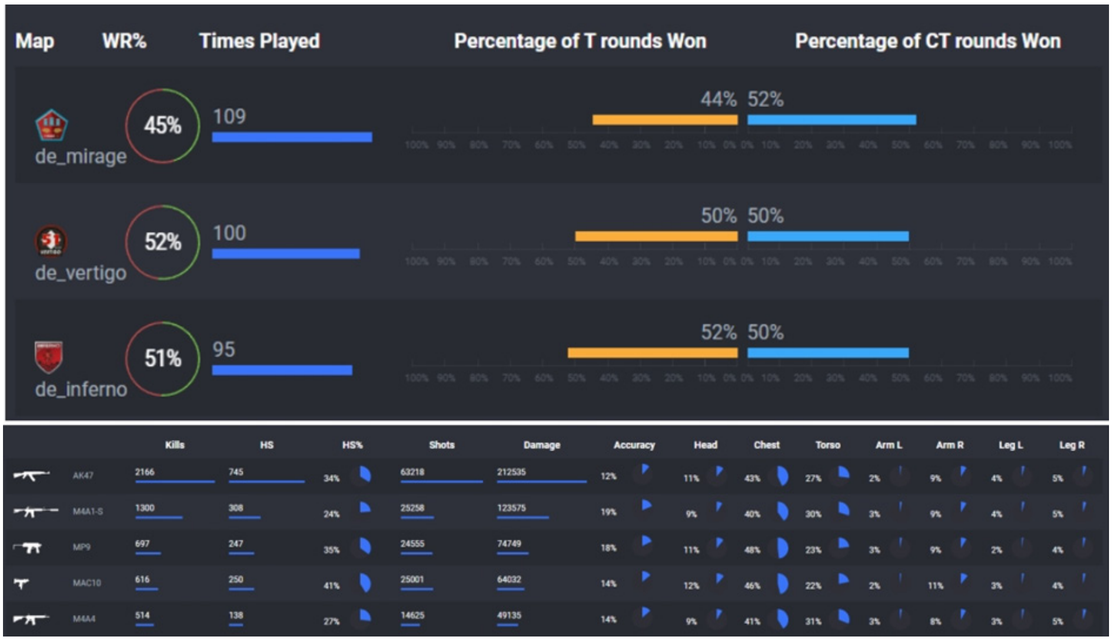
It is also possible to frequently come across data visualization applications in games. Data visualization can be considered in two ways in games. The first of these is the visualization elements that are directly included in the game, such as providing feedback to the user about the game and information about the current game situation. The other is the visualization applications aimed at providing game developers with insight into the user's gaming experience. In Figure 3, data visualization shows the distribution of thrown grenades on a map (Jacobwdym, 2018) over more than 410,000 played rounds in the competitive game Counter-Strike: Global Offensive (CS-GO).

Figure 3
1000 samples of thrown grenades on the left, whole data on the right (Jacobwdym, 2018)



Data visualizations in the game provide the player with a quick and easy-to-understand summary of their status through methods such as dashboards, information panels, and leaderboards, helping them evaluate their current performance and make strategic decisions (Meyer & Bishop, 2022; Ruiperez-Valiente et al., 2021). Thanks to these visualizations, players can monitor their success in the game, notice their areas of development, and plan their future moves more consciously (Danak & Mannor, 2011). In Figure 4, a user's CS-GO gameplay data is displayed, allowing the user to evaluate their performance on three maps and decide which one to improve. Additionally, the user can determine which weapon is best for their gameplay by reviewing their statistics.

Figure 4
CS-GO user game statistics with visuals (CSSTATS (ESL Gaming Online), 2024).



For game developers, data visualization enables the development of better games, in other words, user-friendly designs, by enabling the analysis of how the user behaves and interacts in the game, where they focus more, and the order of the steps in the process (Kriglstein, 2019). Similarly, in order to develop gamification, which is one of the most critical elements in games, data visualization is used to analyze behavioral data in games by combining elements such as points, levels, leaderboards, badges, and challenges to increase user participation and contribution (Yampray & Inchamnan, 2019). Especially visualization of event sequences in games facilitates the understanding of players' skill development, action and timing patterns, and strategy changes, allowing the design of game stages and the examination of player groups (Li et al., 2019). Finally, while data visualization plays an important role in enriching gaming experiences, additional machine learning and AI analytics may need to be implemented to minimize data privacy and misinterpretation risks. With the support of these technologies, more accurate and reliable analytics can be provided, enabling responsible and balanced game design.

Machine Learning Applications in Gaming

In the context of machine learning applications in gaming, advances in areas such as AI-powered NPCs, procedural content generation, game AI, reinforcement learning, and deep learning are enabling gaming environments to become more dynamic, adaptive, and personalized. These technologies not only enhance the complexity of in-game mechanics but also offer novel approaches to content creation and player interaction.

One of the application areas of machine learning in games is creating AI-supported Non-Player Characters (NPCs). Data science plays a pivotal role in the development of NPCs that can adapt to players in real time, enhancing the gaming experience through intelligent behavior and dynamic interactions. The integration of machine learning techniques, particularly reinforcement learning where an agent learns to make decisions by interacting with an environment to maximize cumulative rewards (Merrick, 2008), has been instrumental in creating NPCs that exhibit believable and adaptive behaviors. For example, Cruz and Uresti state that well-developed NPCs that react indistinguishably from human players are crucial to an immersive gaming experience (Cruz & Uresti, 2018). In addition, with the ML-Agent module on Unity (Juliani et al., 2018), and the Learning Agents module on Unreal Engine (Brendan Mulcahy & Daniel Holden, 2023), NPCs can be humanized and made intelligent in the desired direction. This adaptability is further supported by the use of behavior trees, which provide a flexible framework for modeling NPC logic, allowing for more natural interactions and decision-making processes (Kozik et al., 2021). There are two main methods for developing AI-based NPCs, namely task-oriented learning and game-oriented learning (Kaur et al., 2023). Task-driven learning involves agents learning to complete specific tasks in controlled environments based on user-defined goals and action sequences. Game-driven learning occurs in game-like settings where agents learn strategies to win or survive, following the game's rules and constraints.

Another Machine Learning Application used in games is Large language models (LLMs). LLMs can be used to provide real-time feedback and adaptation of game mechanics based on player behavior and avatar interactions. This adaptability can lead to a more engaging gaming environment, where players feel that their actions and choices have significant consequences, further deepening their connection to their avatars and the game world (Taesiri et al., 2022). LLMs can enable NPCs to generate real-time meaningful dialogue, automate narrative creation (Kumaran et al., 2023), personalized gaming experiences, exhibit emotional responses (Garavaglia et al., 2022) and personalities for nuanced interactions (Karpouzis & Tsatiris, 2022), learn and evolve from player interactions (Giunchi et al., 2024), and proactively engage players (Giunchi et al., 2024; Sun et al., 2023) by assigning quests or providing contextual information.

Procedural content generation (PCG) enhances the game development process by making it more dynamic (Bernardi et al., 2021), decreases development time, and makes the in-game experience more adaptive and more replayable (Van Linden et al., 2013). Levels (Z. Zhou & Guzdial, 2021), quests (Soares et al., 2016), and even music (Plans & Morelli, 2012) can be created dynamically through PCG. PCG also helps in reducing the size of game files on the hard drive for customers (Summerville et al., 2017). In his study, Summerville created the machine learning data prepared for PCG through the analysis of the cards that could be collected, level data obtained by frame-by-frame analysis of gameplay videos, and various fictional stories. Level data is seen to be a frequently used data type for machine learning-supported PCG (Khalifa et al., 2020). While 2D game levels are dominant, 3D game levels, story text, rhythm, character models, textures, and cards are also produced by PCG.

In order for games to become more enjoyable and reduce the churn rate, the matchmaking of users must be balanced and competitive. AI can analyze player behavior to match players with similar playstyles. To manage this, the player's historical data can be analyzed to understand the player's behavior, and using this data user levels-styles can be determined (Sapienza et al., 2017). Most of the applications that aim to balance game mechanics and game prediction in games reveal the use of artificial intelligence with machine learning and reinforcement learning methods. Together, machine learning and big data are transforming gaming by improving personalization and dynamic in-game experiences. Machine learning models, like those powering NPC behavior and procedural content generation, generate vast amounts of player data that big data analytics then processes to improve engagement and enhance game mechanics. This combination allows developers to make data-driven adjustments and optimize gameplay based on real-time insights into player preferences and trends.

Big Data Challenges in the Gaming Industry

The concept of big data has gained popularity after the widespread use of the internet and mobile devices, which are vital for daily life. Social media platforms, internet applications, and sensors that obtain data directly from individuals enable the production of large amounts of data and the transformation of the produced data into products. The comprehensive, diverse, and constantly growing data sets contained in big data are quite difficult to process and manage using traditional methods (I. Lee, 2017; Munawar et al., 2020). The main purpose of big data is to obtain general insights from comprehensive data sets and use this information in processes such as data-driven decision-making, predictive analysis, personalized experiences, productivity, and innovation (Sahoo, 2022; Wu et al., 2014).

The increase in the use of the internet and mobile devices has also rapidly expanded the gaming industry, which has a large follower base. The rapid growth of the game sector has also led to an increase in the data produced in games. The main reasons for this are the combination of factors such as the increasing online games, in-game interactions, advanced graphics, the increase in multiplayer games due to the improvement of the internet infrastructure, the increase in the game-playing capacity of mobile devices, and the use of artificial intelligence (Bauckhage et al., 2015; García-Álvarez et al., 2017; Wallner & Drachen, 2023).

Managing and using this big data generated in games has various challenges, primarily due to the enormous volume, variety, and speed of the data generated. For example, companies like Zynga process billions of rows of data every day, which complicates the data management process and analysis (Reynolds, 2019). The diversity of structured and unstructured data generated complicates the extraction of meaningful results, as traditional data management systems have difficulties in accommodating such heterogeneity (Cui et al., 2020). However, as the amount of data generated due to the growing use of online games increases, it is necessary to develop strong infrastructure and analysis processes to ensure timely decision-making (C. H. Lee & Yoon, 2017). At this point, the inherently complex structure of big data can lead to data quality issues such as completeness and accuracy, which are critical for effective analysis (Bandara et al., 2024).

In conclusion, big data technologies significantly enhance the gaming industry by enabling data-driven decision-making and improving user engagement. For example, big companies with millions of users use extensive analytics to understand player behavior and optimize gaming experiences by processing billions of rows of data daily (Reynolds, 2019). Thanks to this data-centric approach, the results developers obtain from game analytics allow them to effectively adapt game features and marketing strategies (Mäntymäki et al., 2020; Su et al., 2022). Additionally, small and medium-sized game developers leverage analytics to improve game designs and revenue forecasts, emphasizing the democratization of data access in the industry (Mäntymäki et al., 2020; Su et al., 2022). On the other hand, the integration of big data encourages innovation by allowing developers to predict trends and user preferences, thereby improving overall gaming sustainability (Na et al., 2022). The rapid increase in data production in the gaming sector has presented both opportunities and challenges. Big data technologies enable developers to gain insights into player behavior, optimize the gaming experience, and drive innovation. However, this also raises ethical and privacy concerns, as extensive data collection and analysis can lead to biased results and privacy risks.

Ethics and Privacy Concerns in Game Data Science

Game data science leverages the amount of data generated by digital games to improve various aspects of the game development process (Seif El-Nasr, 2019). As in any field that processes large amounts of user data, ethical considerations are very important in this field. One of the primary ethical concerns in-game data science is the potential for bias in data-driven decision-making. The datasets used to train algorithms and build models in the game industry may not accurately reflect the full spectrum of player demographics, behaviors, and preferences, potentially leading to biased outcomes that unfairly impact certain groups (Kuhlman et al., 2020). There is a risk of biased data, where certain populations are underrepresented or certain attributes like race, gender, and age are not evenly distributed (Schneider et al., 2023). Therefore, if the developed algorithms are trained on biased data sets, they may unintentionally lead to applications with features aimed at certain groups (Seif El-Nasr & Kleinman, 2020). To address these issues, game developers and data scientists must take proactive steps to ensure that their data-driven practices are transparent and accountable. Players are often unaware of the extent to which their data is collected and used. Based on the information gathered, the ethical considerations in-game data science are not merely an extension of general data ethics but require specific attention due to the unique nature of gaming environments. To solve these problems, consideration should be given to the use of digital approval processes (Charles & Magtanong, 2021).

Game developers and data scientists must work together to create ethical frameworks that consider player behavior and the potential impact of data-driven decisions on the gaming experience. Furthermore, it is essential to foster a culture of ethical awareness within the gaming industry, ensuring that all stakeholders understand the importance of ethical practices in-game data science. To address these concerns, researchers propose developing ethical guidelines, and increasing transparency and accountability (Seif El-Nasr & Kleinman, 2020; Melhart et al., 2024).

Companies collect and use player data to generate revenue and provide better experiences. This situation brings privacy concerns in games (Laakkonen et al., 2016). Modern gaming platforms gather extensive personal information through various means, including hardware sensors, social features, and tracking technologies (Russell, Reidenberg & Moon, 2018). This data collection process raises ethical and privacy concerns about user security, particularly for child gamers (Dasgupta & Sarkar, 2022). Studies show that transparency regarding data practices in the gaming industry is often lacking, especially concerning third-party sharing (Russell, Reidenberg & Moon, 2018). Gamers consider the biggest threats to their privacy while gaming to be the exposure of sensitive information, including passwords, location data, and purchasing or financial details. This data can be collected in-game environments without the knowledge of users, especially through microtransactions (Dasgupta & Sarkar, 2022). To address these issues, researchers suggest incorporating privacy-sensitive approaches into game platform design (Laakkonen et al., 2016) and improving user control mechanisms and privacy settings (Russell, Reidenberg & Moon, 2018).

On the other hand, the integration of AI in gaming brings new ethical challenges, necessitating responsible AI practices (Canca et al., 2024). The gaming industry's growing influence and access to resources come with social responsibilities that have often been neglected (Cook, 2021). Ethical concerns in AI-driven games include the artificial induction of emotions, privacy issues in creating safe gaming spaces, and challenges to transparency and ownership in the game environment (Melhart et al., 2024). To address these challenges, the gaming industry needs to adopt responsible AI practices, tools, and governance structures (Canca et al., 2024). As the ethical and privacy aspects of game data science continue to grow in importance, the integration of AI and advanced data processing methods is making the process more complex and providing new opportunities. At the same time, emerging trends such as edge computing, "living games" with ever-evolving NPCs, and blockchain-based assets are creating a dynamic space that enhances user experience and data-driven interaction. These innovations and more will shape the next generation of immersive, personalized, and emotionally intelligent gaming experiences, where ethical frameworks, AI applications, and innovative technologies converge.

Future Trends: AI and Data Science in Gaming

Edge computing offers solutions to latency and bandwidth problems in gaming environments by making computing resources accessible to users (Hammad et al., 2023). Real-time Edge computing is particularly useful for mobile augmented reality (AR) games that require high responsiveness and processing power (Hammad et al., 2023). Besides, edge computing is also useful for video streaming that requires high bandwidth and low latency (Bilal & Erbad, 2017). Applications such as real-time video analytics, vehicle applications and multi-user cloud games, and smart city technologies will benefit more from edge computing in the future (L. Lin et al., 2019). These developments can improve user experience and open up new possibilities in gaming environments.

Another concept that data analysis and AI have revealed in-game environments is the concept of "living games". The concept of "living games" with dynamic Non-Playable Characters (NPCs) that evolve, and interact in real time, is becoming increasingly feasible thanks to advancements in AI and procedural content generation (Cruz & Uresti, 2018). Generative AI models like GPT-4 enable more immersive experiences by allowing NPCs to engage in real-time, unscripted conversations. For instance, systems like PANGeA use generative AI to allow NPCs to develop personalities and exhibit human-like traits based on psychological models. This enables NPCs to continue interacting and evolving even when the player is not in the game, making the game world feel more alive. Players might return to the game to find that NPCs have developed new relationships or knowledge based on their own activities, independent of player intervention (Buongiorno et al., 2024).

Another technology that is expected to increase its impact in the gaming world is blockchain technology. Thanks to blockchain, a more secure and transparent process can be provided in the management of in-game assets of NFTs (Non-Fungible Tokens). NFT-based in-game assets can provide users with a greater sense of ownership of digital assets and therefore digital games by ensuring that each asset is unique and its ownership can be verified on the blockchain. (Paajala et al., 2022; Paduraru et al., 2022). Thanks to the infrastructure provided by blockchain, it is also easier to create a shared marketplace and digital wallet. Such marketplaces can allow players to securely buy and sell the digital assets they earn or obtain, and even move them between different games (Paduraru et al., 2022). Play-to-earn models, in particular, allow players to directly convert in-game assets and services into money. In this way, the gaming experience can be evaluated not only for entertainment but also as economic gain. These opportunities offered by Blockchain will also provide game developers with the opportunity to create new business models. Developers can leave control of the assets in the game to the players, allowing the assets to be traded even in markets outside the game. Such developments will enable the expansion of game ecosystems to a wider universe and improve player experiences (Paajala et al., 2022).

On the other hand, studies are being conducted to investigate the nature of the emotions evoked by video games, how emotions are produced through games, and how games can be used for emotion regulation (Hemenover & Bowman, 2018). Studies have suggested conceptual frameworks for emotional design and emphasized the importance of understanding emotions in order to create interesting environments (de Byl, 2015; Hemenover & Bowman, 2018). Challenges in this field include developing intelligent systems capable of accurately interpreting players' emotional states and adjusting game narratives accordingly (Kotsia et al., 2013). Looking forward, Kotsia et al. (2013) argue that affective gaming holds the potential to transform player-game interactions. Imagine a game that can sense when a player is feeling frustrated and automatically offers assistance, or one that increases the emotional intensity of a scene based on the player's response. Moreover, as more studies focus on the relationship between games and emotions, the development of emotionally intelligent games could lead to innovations in game design, creating more empathetic and emotionally resonant gaming worlds. Thus, the future of emotional engagement in games will not only enhance entertainment but also support emotional growth, offering new ways for players to connect with games on a personal and emotional level.

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